Design of an Autonomous Intelligent Demand-Side Management System by using Electric Vehicles as Mobile Energy Storage Units by Means of Evolutionary Algorithms

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Abstract: Evolutionary Algorithms (EAs), or Evolutionary Computation, are powerful algorithms that have been used in a range of challenging real-world problems. In this paper, we are interested in their applicability on a dynamic and complex problem borrowed from Demand-Side Management (DSM) systems, which is a highly popular research area within smart grids. DSM systems aim to help both end-use consumer and utility companies to reduce, for instance, peak loads by means of programs normally implemented by utility companies. In this work, we propose a novel mechanism to design an autonomous intelligent DSM by using (EV) electric vehicles' batteries as mobile energy storage units to partially fulfill the energy demand of dozens of household units. This mechanism uses EAs to automatically search for optimal plans, representing the energy drawn from the EVs' batteries. To test our approach, we used a dynamic scenario where we simulated the consumption of 40 and 80 household units over a period of 30 working days. The results obtained by our proposed approach are highly encouraging: it is able to use the maximum allowed energy that can be taken from each EV for each of the simulated days. Additionally, it uses the most amount of energy whenever it is needed the most (i.e., high-peak periods) resulting into reduction of peak loads.

1 INTRODUCTION

Evolutionary Algorithms (EAs) (Bäck et al., 1999; Eiben and Smith, 2003), also known as Evolutionary Computation systems, are influenced by the theory of evolution by natural selection. These algorithms have been with us for some decades and are very popular due to robust theoretical work developed around them that have helped us to understand why they work (e.g, representations' properties (Galván-López et al., 2010a; Fagan et al., 2010; Galván-López et al., 2008; McDermott et al., 2010)) and to due to their successful application in a variety of different problems, ranging from the automated design of an antenna carried out by NASA (Lohn et al., 2005), the automated optimisation of game controllers (Galván-López et al., 2010b), the automated evolution of Java code (Cody-Kenny et al., 2015), to automated design of combinational logic circuits (Galván-López et al., 2004; Galván-López, 2008). EAs can be considered a "black-box", as they do not require any specific knowledge of the fitness function. They work even when, for example, it is not possible to define a gradient on the fitness function or to decompose the fitness function into a sum of per-variable objective functions.

In this work, we are interested in investigating the applicability of EAs in a dynamic and challenging problem in Demand-Side Management (DSM) Systems taken from Smart Grids where, in summary, the goal is to automatically create fine-grained solutions that indicate the amount of energy that can be taken from electric vehicles' (EVs) batteries to partially satisfy energy demand in residential areas and reducing electricity peaks, whenever possible. The proposed approach and fitness functions used in our work (described in Section 2) is not amenable to analytic solution or simple gradient-based optimisation, hence search algorithms such as EAs are required.

DSM is normally considered as a mechanism or program, implemented by utility companies, to control the energy consumption at the customer side (Masters, 2004). DSM is an important research

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area in the Smart Grid (SG) community as shown by the increasing number of publications over the years (e.g., more than 2,000 papers have been published in this area where more than two thirds have been published since 2010 (Galván-López et al., 2014)). A visual representation of the research conducted in DSM over the last years can be found in (Galván-López et al., 2015).

DSM programs include different approaches (e.g., manual conservation and energy efficiency programs (pen, 2007), Residential Load Management (RLM) (Galvan et al., 2012; Mohsenian-Rad et al., 2010)), where RLM programs based on smart pricing are amongst the most popular methods. The idea behind smart pricing is to encourage users to manage their loads, so that they can reduce electricity prices while, at the same time, the utility companies achieve a reduction in the peak-to-average ratio (PAR)[1] in load demand by shifting consumption whenever possible (Galvan et al., 2012; Galván-López et al., 2014).

One of the major limitations of smart pricing is the fact that the electricity price is proportional to the electricity demand (i.e., a high number of appliances/devices connected to the grid results in having high electricity costs). To alleviate this problem, we propose the development of a demand-side *autonomous intelligent* management system that exploit electric vehicles' (EV) batteries. More precisely, our system uses the EV's batteries to partially and temporarily fulfill the demand of end-use consumers instead of using only the electricity available from a substation transformer. This is possible thanks to the vehicle to grid (V2G) technology, which is described as a system in which electric-drive vehicles can feed power to the grid with the appropriate communication/connection technologies acting as mobile generators of limited output (Kempton and Letendre, 1997; Kempton and Tomic, 2005).

The deployment of such a system implies several significant challenges, e.g. different driving patterns resulting in the amount of energy needed at the time of departure, amount of energy taken from the EVs' batteries. To tackle this problem, we use an optimisation EA.

Thus, the main contribution of this research is a novel approach to balance the load demand from dozens of household units using both a substation transformer and EVs' batteries as mobile energy storage units[2] by considering the *automatic* generation of solutions via the use of EAs. To this end, we are interested in maximising, in general, the use of available energy from the EVs' batteries while ensuring that each of the EVs can complete a journey to work, where the EVs can be charged, and in particular, helping in the reduction of peak loads at the transformer level by using the most quantity of energy from the EVs' batteries. This problem would be simple enough if it was not for the dynamicity associated to the problem and if we would not care about keeping the PAR relatively low.

To achieve this, we allow the DSM system to make fine-grained decisions (i.e., variable amount of energy requested) by using a continuous representation instead of using a discrete representation (i.e., turning a device/appliance on or off resulting in feeding/getting a constant amount of energy) as normally adopted in DSM (Brooks et al., 2010).

To this end, we use a form of EAs, called Differential Evolution (DE) (Storn and Price, 1997), that allows us to achieve this. More specifically, DE uses a vector of real-valued functions and we use them to represent an individual (potential solution) that specifies an energy consumption scheduling vector, which in turn indicates the amount of energy that should be taken from the EVs' batteries aiming at fulfilling the goals previously described (e.g., maximising the energy consumption available from the batteries while at the same time reducing peak loads at the transformer level with associated constraints such as guaranteeing that each EV would complete a journey to work). Details on how this algorithm works and its adoption in this research are described in Section 2.

The rest of this paper is organised as follows. In the following section we introduce DE and present our proposed approach. In Section 3, we present the experimental setup used in this work and Section 4 discusses the findings of our approach. Finally, in Section 5 we draw some conclusions.

2 PROPOSED APPROACH

2.1 Background

There are multiple EAs methods, such as Genetic Algorithms (GAs) (Goldberg, 1989), Genetic Programming (GP) (Koza, 1992), Differential Evolution (DE) (Storn and Price, 1997). All these methods use evolution as an inspiration to automatically generate potential solutions for a given problem. They differ,

[1] Peak-to-average ratio is calculated by the maximum load demand for a period of time over the average load demand, so a lower PAR is normally preferred due to e.g. maintenance costs (Mohsenian-Rad et al., 2010).

[2] In this work, we use the terms "substation transformer" and "EV's batteries" to differentiate between the two sources of energy.

mainly, in the representation used (i.e., encoding of a solution). For example, the typical representation used in GAs is fixed bitstrings, GP's typical representation is tree-like structures, DE uses a vector of real-valued functions.

In this work, we use a DE algorithm given its natural representation (i.e., real-valued functions). Other bio-inspired algorithms can also use this type of representation, however, in this work we decided to use a DE given its efficiency for global optimisation over continuous search spaces (Storn and Price, 1997). By using this type of representation, we can have a more fine-grained action granularity (e.g., in this work, each element in the vector represents how much energy will be taken from the EVs' batteries to feed household units), instead of using a more limited representation such as a bitstring representation that could indicate to take a pre-defined amount of energy (i.e., on or off) from EVs' batteries to partially fulfill energy consumption from household units. We further discuss this later in this section.

The goal of DE is to evolve *NP* *D*-dimensional parameter vectors $x_{i,G} = 1,2,\cdots,NP$, so-called population, which encode the potential solutions (individuals), i.e., $x_{i,G} = \{x^1_{i,G} \cdots, x^D_{i,G}\}, i = 1,\cdots,NP$ towards the global optimum solution (e.g., highest values when maximising a cost function). The initial population is randomly generated and this should be done by spreading the points across the entire search space (e.g., this could be achieved by distributing each parameter on an individual vector with uniform distribution between lower and upper bounds x^l_j and x^u_j). To automatically evolve these potential solutions over generations via the definition of a fitness function, DE uses the most common bio-inspired operators as commonly carried out in EAs: mutation and crossover to find the global optimum solution. Each of these operators is briefly explained in the following lines (refer to (Qin et al., 2009; Storn and Price, 1997) for a detailed description on how they work).

The mutation operator generates a mutant vector following one of the following strategies:
DE/rand/1

$$v_{i,G} = x_{r^i_1,G} + F \cdot (x_{r^i_2,G} - x_{r^i_3,G})$$

DE/best/1

$$v_{i,G} = x_{best,G} + F \cdot (x_{r^i_1,G} - x_{r^i_2,G})$$

DE/rand-to-best/1

$$v_{i,G} = x_{i,G} + F \cdot (x_{best,G} - x_{i,G}) + F \cdot (x_{r^i_1,G} - x_{{}^i_2,G})$$

DE/best/2

$$v_{i,G} = x_{best,G} + F \cdot (x_{r^i_1,G} - x_{r^i_2,G}) + F \cdot (x_{r^i_3,G} - x_{r^i_4,G})$$

DE/rand/2

$$v_{i,G} = x_{r^i_1,G} + F \cdot (x_{r^i_2,G} - x_{r^i_3,G}) + F \cdot (x_{r^i_4,G} - x_{r^i_5,G})$$

where indexes r_1, r_2, r_3, $r_4 \in \{1,2,\cdots,NP\}$ are random and mutually different. F is a real and constant factor $\in [0,2]$ for scaling differential vectors and $x_{best,G}$ is the individual with best fitness value (e.g., highest value for a maximisation function) in the population at generation G.

The crossover operator increases the diversity of the mutated parameter vectors and is defined by:

$$v_{i,G+1} = (v_{1i,G+1}, v_{2i,G+1}, \cdots, v_{Di,G+1})$$

where:

$$v_{ji,G+1} = \begin{cases} v_{ji,G+1} & \text{if } randb(j) \le CR \text{ or } j = rnbr(i), \\ x_{ji,G} & \text{otherwise} \end{cases}$$

where $j = 1,\cdots,D$, $randb(j)$ is the jth evaluation of a uniform random number generator with outcome $\in [0,1]$. CR is the constant crossover rate $\in [0,1]$. $rnbr(i)$ is a randomly chosen index $\in 1,2,\cdots,D$ which ensures that $u_{i,G+1}$ receives at least one parameter value from $u_{i,G+1}$.

The performance of the DE algorithm depends on different factors, such as the values associated to the parameters (e.g., population size) as well as the variant of the operator used (e.g., variant of the mutation operator). This, intuitively means, that some preliminary runs would be normally required to determine which variant of an operator performs better on a given problem. We further discuss this in the following section.

2.2 Proposed Representation and Fitness Function

We now extend the natural DE representation to tackle the problem described throughout the paper and proceed to define the fitness function (cost function) that allows the algorithm to automatically guide the evolutionary search.

Let N denote the number of household units (users), where the number of household units is $N \triangleq | N |$. For each household $n \in N$, let l^t_n denote the total load at time $t \in T \triangleq \{t_i,\cdots,t_f\}$. Without loss of generality, we assume that time granularity is 15 minutes. The load for household n, from t_i to t_f, is denoted by:

$$l_n \triangleq [l^{t_i}_n, \cdots, l^{t_f}_n] \quad (1)$$

From this, we can calculate the load across all household units N at each time $t \in [t_i, t_f]$ as follows:

$$L_t \triangleq \sum_{n \in N} l^t_n \quad (2)$$

Similarly, let M denote the number of electric vehicles available in N. For each electric vehicle $m \in M$, let E_m^t denote the energy that can be taken from the EV at time $t \in T \triangleq \{t_i, \cdots, t_f\}$. Without loss of generality, we assume that time granularity is again 15 minutes. The total energy taken from an EV from t_i until t_f is denoted by:

$$E_m \triangleq [E_m^{t_i}, \cdots, E_m^{t_f}] \quad (3)$$

We use this as a foundation to represent an individual that specifies an energy consumption scheduling vector. More specifically, an individual is represented by:

$$E_M \triangleq \begin{bmatrix} E_{m_1}^{t_i}, \cdots, E_{m_1}^{t_f} \\ E_{m_2}^{t_i}, \cdots, E_{m_2}^{t_f} \\ \vdots \\ E_{m_M}^{t_i}, \cdots, E_{m_M}^{t_f} \end{bmatrix} \quad (4)$$

where each E_M^t is a real value representing the amount of energy taken from an EV's battery. Each row represents the behaviour of a single EV over the full period; each column represents the behaviour of all EVs at a single time-slot. An individual in the EA is just a matrix E_M, unrolled to give a vector of real-valued functions, that is:

$$E_1^{t_i}, \cdots, E_1^{t_f}, E_2^{t_i}, \cdots, E_2^{t_f}, \cdots, E_M^{t_i}, \cdots, E_M^{t_f} \quad (5)$$

Based on these definitions, the total energy taken across all M EVs at each $t \in [t_i, t_f]$ can be calculated as:

$$E_t \triangleq \sum_{m \in M} E_m^t \quad (6)$$

To automatically find good energy consumption scheduling solutions, defined in Equation 4, we need to define a fitness function (cost function) that indicates the quality of our evolved solution. First, we focus our attention in designing a cost function that tries to create valid solutions in terms of using the maximum allowed energy from each EV (i.e., guaranteeing that a minimum state of charge (SoC) is left at the time of departure t_f).

From Equation 3, we know the amount of energy available from $m \in M$ at any given period of time t denoted by E_m^t. Because each EV can be charged at work and the distance from home to work remains constant, it is fair to assume the knowledge of a minimum SoC expressed in kW, denoted as m_{SoC}, at the time of departure t_f for each $m \in M$, so that it can reach work and be recharged at a lower rate. From this, we let the DE to assess a potential solution, denoted in Equation 4, measuring the amount of energy taken from the EVs.

This is defined as:

$$f_l(E_M) \triangleq \textbf{maximise} \quad \frac{1}{\#\{m \in M\}} \sum_{m \in M} \frac{E_m + (E_m + 1)(m_{SoC} - E_m^{t_i})}{m_{SoC}\left(E_m^{t_i} - m_{SoC}\right)} \quad (7)$$

Equation 7 guides evolutionary search towards a local optimum solution since it only encourages the finding of solutions that maximise the use of allowable energy taken from EVs' batteries. Thus, there is a necessity to further enrich this equation, so that a higher quantity of energy is taken from the EVs' batteries whenever deemed necessary (e.g., higher consumption during high peak periods). We achieve this by using Equations 2 and 6 that indicate the load across all household units L_t at time t and the total energy taken across all EVs E_t at time t, respectively; and we define a degree of importance for each time slot as t_r. Putting everything together we have:

$$\begin{aligned} f_g(E_M) \triangleq f_l(E_M) + \ & \textbf{maximise} \\ & \frac{1}{\#\{m \in M\}} t_r \sum_{t=t_i}^{t_f} \frac{E_t}{L_t t_r} \forall t_r < T_r - \\ & \frac{1}{\#\{m \in M\}} t_r \sum_{t=t_i}^{t_f} \frac{E_t}{L_t t_r} \forall r \geq T_r \end{aligned} \quad (8)$$

where T_r is a threshold that denotes the number of time slots that are considered critical (i.e., high peak period). In this work, as defined in this section and we discuss further afterwards, a number of time slots is defined by t_i and t_f, where a third is considered critical ($T_r = 20$).

3 EXPERIMENTAL SETUP

3.1 Household Units

To test the scalability of our proposed approach, we simulated the consumption of 40 and 80 household units, where each of them uses between 10 and 20 appliances. As indicated throughout the paper, the goal is to use EVs' batteries in an intelligent way to partially satisfy energy demand from the end-use consumers (recall that we work under the assumption that the EVs can be charged at work).

To this end, we simulated that around 20% of household units account for an EV. To make this problem dynamic, we allowed the patterns of arrival (t_i), departure (t_f) and initial State of Charge (*SoC*) for each of the EVs to vary for each of the 30 simulated working days. More specifically, the arrival and departure time for each of the EVs have a 90-minute time frame starting at t_i =17:00 and t_f =6:30, respectively (i.e., arrival time could be between 17:00 and 18:30, whereas departure time could be between 6:30 and 8:00). The initial SoC_{t_i} for each of the EVs for each of the simulated days is set between 48% and 60% and the final SoC_{t_f} is set between 30% and 35% to allow each EV to reach work. Table 1 summarises the parameters used to simulate our scenario. We ran our simulations for a period of 30 days of simulated time.

3.2 Scenarios

As indicated in Section 2, we defined a bottom-up approach, where we defined, first, a fitness function that tries to maximise the energy that can be taken from the EVs' batteries while ensuring that each of them reaches work, described in Equation 7, and then we enriched the fitness function by trying to also reduce the highest load demands at the substation transformer, described in Equation 8 (i.e., use the most amount of energy from the batteries at high-peak time while at the same time ensuring the PAR remains low). We tested both fitness functions for 40 and 80 household units, resulting in four different scenarios.

3.3 Differential Evolution

As mentioned in Section 2, differential evolution's performance, as any other evolution-based algorithm, depends, among other things, on the values associated to the parameters that need to be specified for the algorithm (e.g., population size, number of generations), in general, and in the type of operator used, in particular.

No *a priori* knowledge is available to presume which mutation operator will perform better in the previously defined problem. To this end, we executed 30 independent runs of our proposed approach for each of the mutation variants, e.g., DE/rand/1, DE/best/1, (150[3] independent runs in total to find only the best mutation strategy) using the first proposed fitness function (Equation 7) which maximises the energy taken from 11 EVs' batteries to complement the energy consumption of 40 household units averaged over 30 days. Figure 1 shows the performance by measuring the average of best fitness per generation for each of the five mutation variants, using a population size of 500 individuals and 200 generations.

Clearly, the mutation strategy DE/rand/2 achieved the best performance and we used it to run our experiments to automatically find a (nearly) optimal solution. To obtain meaningful results, we performed 30 independent runs for each of the scenarios explained in the previous paragraphs (we executed 30 * 4 runs in total[4]). Runs were stopped when the maximum number of generations was reached.

[3] 30 independent runs * 5 variants of the mutation operator.

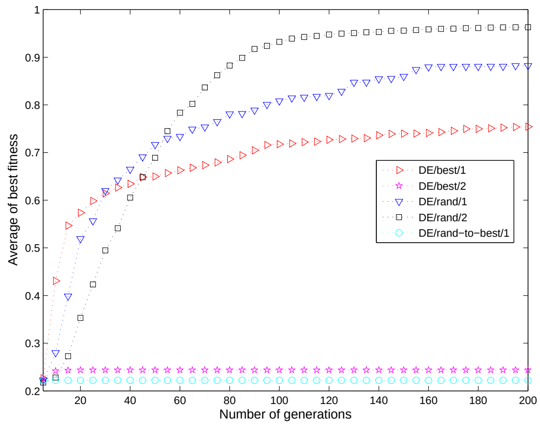

Figure 1: Average of best fitness values of 30 independent runs for each of the five types of mutation operators tested in this work, using 500 individuals and 200 generations, to maximise energy consumption from electric vehicles' batteries (Equation 7). Higher values are preferred.

As mentioned in Section 2, every element of the DE vector represents how much energy can be taken from the batteries of the EVs. We make a decision every 15 minutes. Thus, the length of the individual that represent the solution is the number of time slots defined between 17:00 and 8:00am, whereas the height is defined by the number of electric vehicles used, as defined in Equation 4. The parameters used in our experiments are summarised in Table 2.

4 RESULTS

In the following paragraphs, we will analyse: (a) how the EVs' batteries were used to partially satisfy the demand of a set of household units, (b) when the highest consumption from EVs' batteries occurred, and finally, (c) the implications of the new consumption model via the analysis of the peak-to-average-ratio.

4.1 Maximising Energy Consumption from EVs' batteries

Let us start analysing our approach on how the

[4] 30 independent runs, 4 different scenarios (i.e., 40 and 80 household units, trying to maximise: (a) energy consumption from EVs, and (b) energy consumption from EVs considering reducing highest load peaks; for each of the set of household units used in this work).

Table 1: Summary of parameters used for our smart grid system.

Parameter	*Value*
Number of household units	40, 80
Number of appliances	Uniform in [10,20]
Number of EVs	$\approx$ 20% of houses have one EV
Arrival and departure time	t_i =[17:00,18:30] t_f =[6:30,8:00]
Frequency of making a decision	15 minutes
Number of times slots T	60
State of Charge at t_i	Uniform in $[48,60]$
State of Charge at t_f	Uniform in $[30,35]$

Table 2: Summary of parameters used for our evolutionary algorithm.

Parameter	*Value/Comment*
Population size	500
Length of the chromosome	T (see Table 1)
Height of the chromosome	Number of EVs (see Table 1)
Generations	200
Crossover rate	0.5
Mutation strategy	DE/rand/2
Termination criterion	Maximum number of generations
Independent runs	30

batteries of the EVs helped to partially satisfy the consumption demand from a set of household units. The averaged consumption over a period of 30 days of these household can be seen in Figure 2 (a, b) and (c, d) for 40 and 80 houses, respectively.

In the left-hand side of this figure, we show the distribution of consumption of both transformer and EVs' batteries proposed by the differential evolution algorithm, when trying to maximise the consumption of energy from the EVs' batteries via Equation 7. More specifically, it aims at using all the possible energy available from the batteries while guaranteeing that each EV has a minimal SoC at the time of departure (see Table 1) that guarantees that each EV will reach work. The white-filled bars represent the energy taken from the substation transformer whereas the remaining energy consumption to fulfill the energy demand is taken from the EVs' batteries. The latter is shown by the black-filled bars.

Because we are interested in using the EVs' batteries as mobile energy storage units, we are particularly interested in seeing how the energy consumption from these is managed by the differential evolution algorithm. In the first instance of our algorithm (i.e., maximising the energy consumption from the batteries of EVs with associated constraints, as mentioned previously), it is expected that the energy taken from the batteries would not follow a particular pattern (e.g., there is no correlation between the amount of energy consumption from EVs and the energy needed by a number of household units). Indeed, this is the case as seen in the left-hand side of Figure 2. For example, notice how the consumption from EVs' is proportionally similar during both high-peak (e.g., 18:30 - 19:30) and low-peak periods (e.g., 22:00 - 23:00).

The situation is more encouraging when we consider the second instance of our algorithm (i.e., maximising energy consumption from EVs' batteries while considering high-peak periods), shown in the right-hand side of Figure 2. As it can be observed, the proposed enriched fitness function, shown in Equation 8, is able to automatically produce results that can reduce the load peaks from the substation transformer by using more electricity from the EVs' batteries. For example, notice how the consumption of energy from batteries is higher during high-peak periods (e.g., 18:30 - 19:30) and lower during low-peak periods (e.g., 22:00 - 23:00).

4.2 Consumption from EV's batteries

In the previous paragraphs, we discussed and showed the results obtained by our approach using two cost functions, formally described in Equations 7 and 8. It is clear that the latter function is able to use a higher quantity of energy from the EVs' batteries during high-peak periods compared to the effects when using the former function, as shown in the right-hand and left-hand side of Figure 2, respectively, using 40 and 80 household units. This averaged result over a period of 30 simulated working days, however, does not inform us in detail when the highest consumption from batteries occurred (e.g., when and how much consumption from the batteries for every of the simulated days occurred).

To this end, we kept track of the consumption from the EVs' batteries during the simulated period of time (i.e., 17:00 - 8:00) for every day of the simulated days. The patterns of such consumption are shown in Figure 3 (a, b) and (c, d) for 40 and 80 household units, respectively.

Let us start our analysis when maximising the energy that can be taken from the batteries while ensuring that each EV has the minimum SoC at the time of departure, defined in Equation 7. The consumption pattern of this is shown in Figure 3 (a) and (c) for 40 and 80 household units, respectively. It should be noted that the higher the consumption from batteries is, the darker the dot. We can see that a random pattern is achieved by the cost function shown in Equation 7. That is, for every recorded day, shown in the *y*-

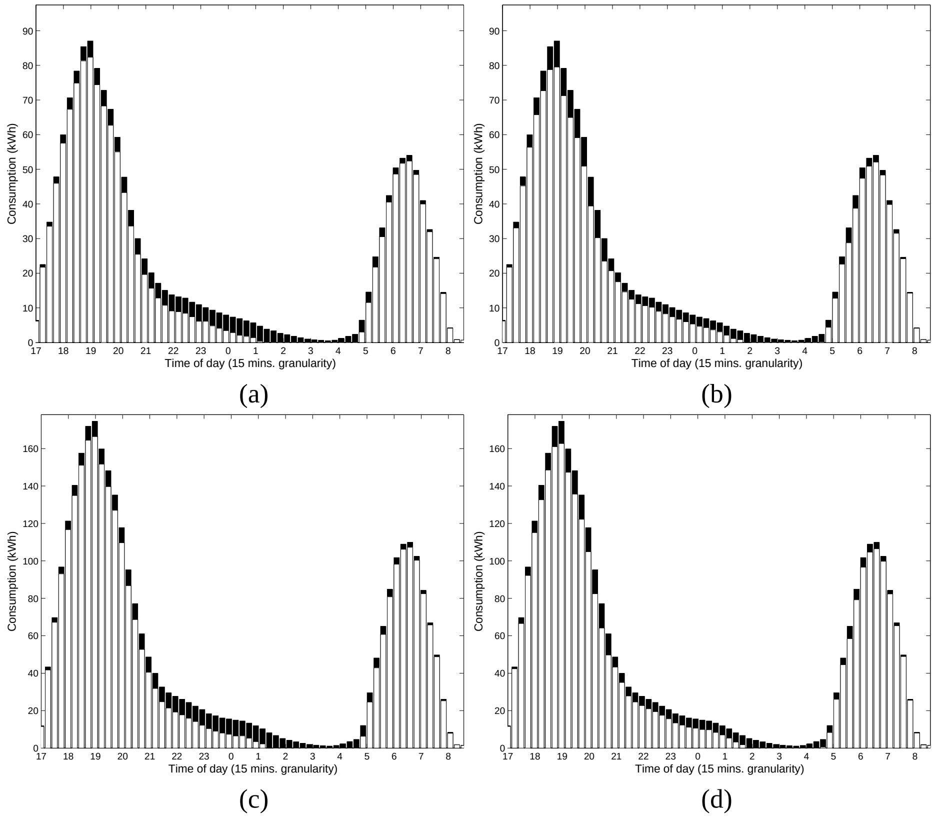

Figure 2: Average of 30-day energy consumption for 40 (top) and 80 (bottom) household units, each using between 10-20 appliances. The consumption of energy from the transformer alone is shown by the white-filled bars whereas the black-filled bars represent the consumption taken from electric vehicles' batteries. Maximising energy consumption from electric vehicles only and maximising energy consumption from electric vehicles considering reducing highest load peaks are shown in the left-hand side and right-hand side of the figure, respectively.

axis, the amount of energy taken from the batteries is rather random regardless of the period time, shown in the *x*-axis, except from 17:00-18:30 and 6:30 – 8:00, where the consumption from batteries is low. This can be explained due to the availability of EVs during these periods. That is, as indicated in Section 3, each EV has its own time of arrival and departure which varies during these periods of time.

We continue our analysis on the proposed enriched maximisation cost function, see Equation 8, that aims at using the most amount of energy from the batteries of the EVs while ensuring that each has a minimum SoC at the time of departure, and that tries to reduce the highest peak loads. The consumption pattern from the batteries is shown in Figure 3 (b) and (d) for 40 and 80 household units, respectively. This is a mirror image of what we discussed in the previous paragraph. That is, there is a well-defined pattern for each of the simulated days, shown in the *y*-axis, during the period of study, shown in the *x*-axis of the figure. We can observe that this cost function indeed achieves at using the most amount of energy when it is needed the most (high-peaks) as shown by the darker-filled squares while ensuring that the constraints are not violated (e.g., minimum SoC at the time of departure).

4.3 Peak-To-Average Ratio

As indicated previously, the peak-to-average ratio (PAR) is calculated by the maximum load demand for a period of time over the average load demand for the same period. It has been shown that a lower PAR is preferred (Mohsenian-Rad et al., 2010).

We calculated the PAR considering the consumption from the substation transformer. Figure 4 shows the PAR for 40 (left-hand side) and 80 (right-hand side) household units for each of the 30 working simulated days using our proposed approach. It is easy to observe that a higher PAR is achieved by the fitness (cost) function formally defined in Equation 7, which goal is to use the most amount of energy from EVs' batteries while at the same time aims at guaranteeing that each EV has a minimum SoC at the time of depar-

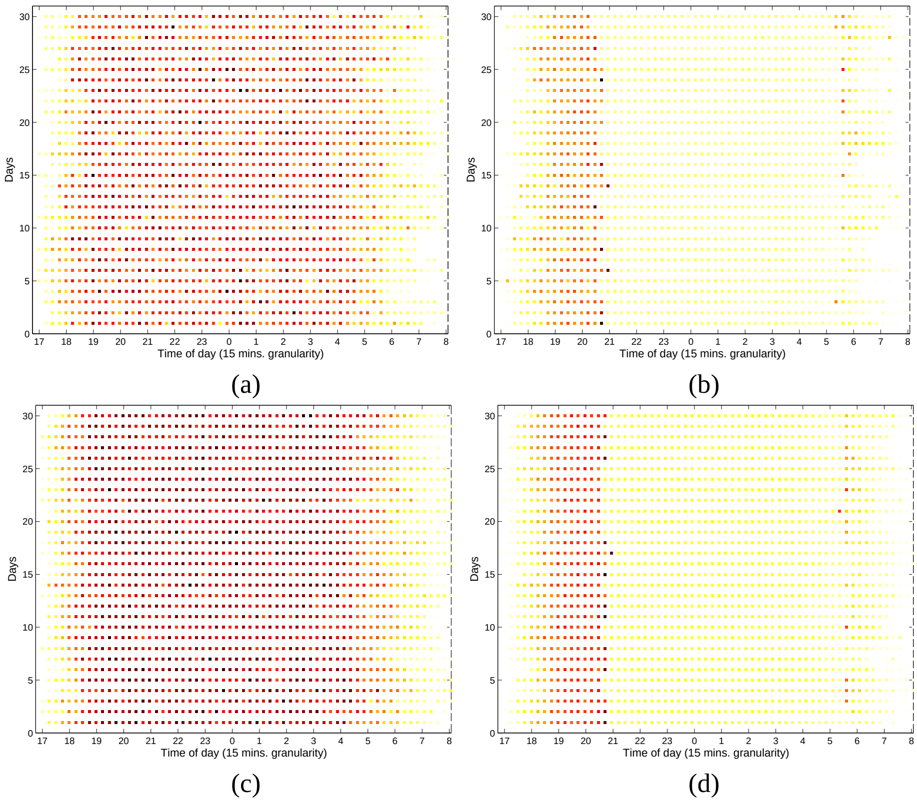

Figure 3: Energy quantity taken from 11 (a, b) and 21 (c, d) electric vehicles over the range of time period studied in this work, from 17:00 until 8:00 (shown in the x-axis), for 30 days (shown in the y-axis) to help with the energy consumption of 40 (a, b) and 80 (c, d) household units. Darker-filled circles represent higher energy quantity taken from the EVs' batteries. The enriched cost function, described in Equation 8, follows a well-defined desired pattern (b, d), whereas the cost function that tends to find local optimum solutions, described in Equation 7, tends to have a rather undesirable random pattern (a, c).

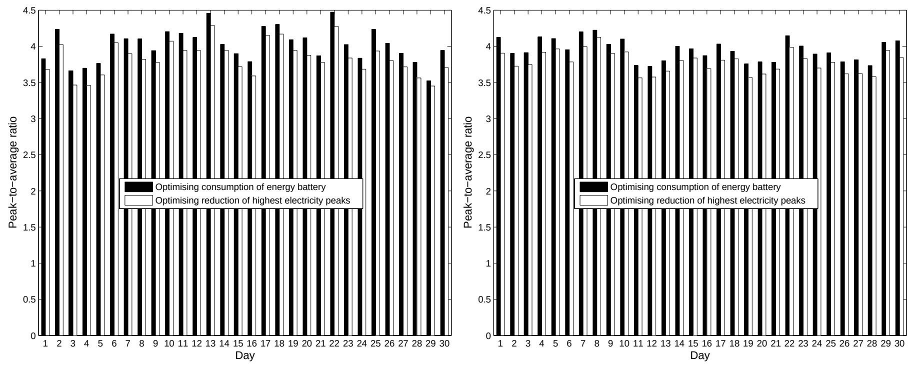

Figure 4: Peak-to-average ratio (PAR) load demand achieved by our proposed approach when trying to maximise energy consumption from EVs' batteries (black-filled bars) vs. when trying to maximise energy consumption from EVs' batteries while aiming at reducing highest load peaks (white-filled bars), for 40 and 80 household units shown at the left-hand side and right-hand side of the figure, respectively. A lower PAR is preferred.

ture compared to that PAR achieved by the enriched fitness function formally described in Equation 8 that is built on the top of Equation 7, which also tries to reduce the highest peak loads.

This, in fact, is to be expected given that the fitness function described in Equation 8 does consider an associated ranking system (recall that a third of time slots are considered critical, i.e., high peak period) that is able to reflect smoothly the consumption from the substation transformer as shown by the low PAR achieved by this enriched fitness function for each day of the 30 simulated days, denoted by the white-filled bars in Figure 4.

5 CONCLUSIONS

Evolutionary Algorithms are very popular given its applicability in a range of static problems. In this work, we focus our attention on using a differential evolution (DE) algorithm in a fairly complex and dynamic problem taken from Demand-Side Management (DSM) systems. DSM systems play an important role in the SG. Their importance can be understood by considering the new challenges that are continuously introduced to the grid, for example, electric appliances that could double the average household (e.g., electric vehicles). The correct design of a DSM manages to use the available energy efficiently, without the necessity of installing new electricity infrastructure.

In the specialised literature, there are several techniques adopted by DSM programs. Perhaps, the most popular techniques are those inspired on smart pricing. Briefly, the idea is to incentivise end-consumers to shift energy consumption to hours when the electricity price is low, reducing both electricity costs and energy-load consumption.

We believe that another important research area worth exploring in DSM is to exploit "new" available technologies. In particular, we regard that there is a lot of potential in utilising EVs' batteries as mobile energy storage units. To this end, we propose a demand-side *autonomous intelligent* management system that uses them to partially fulfill the demand of end-use consumers instead of using only the electricity available from a substation transformer, whenever possible. To this end, we use a DE algorithm, that is able to automatically create fine-grained solutions that indicate the amount of energy that can be taken from the EVs, rather than adopting a more constraint representation (e.g., on/off of EVs).

The results achieved by our proposed approach are highly encouraging. That is, we showed how DE is able to correctly use the maximum amount of energy while ensuring a minimum SoC for each EV for each day of the 30 simulated working days. We built upon this to automatically find the best possible configuration of values (i.e., consumption from batteries) whenever it was needed the most (i.e., high-peaks), while simultaneously, demonstrating that it was possible to do so by keeping the PAR low.

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